Stockholm School of Economics
Department of Economics
5350 Master's thesis in economics
Spring 2026

Mandatory CSR Allocation and Rainfall Shocks: Evidence from Indian Districts

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Abstract - This paper studies whether India's mandatory CSR regime reallocates geographically toward districts experiencing adverse monsoon rainfall shocks, using data from 605 Indian districts for 2016–2023. A drought is associated with approximately 11 to 14 percent higher CSR spending in the following year. The corresponding excess-rain response is positive but smaller and not consistently significant. The drought response is concentrated in poorer districts, approximately doubling at one standard deviation above mean multidimensional poverty. State-assembly elections held in the second half of the year are independently associated with higher CSR spending, and the lagged drought effect survives controls for election timing. The effect does not extend to per-resident or aggregate CSR spending and is sensitive to specification. These findings suggest that mandatory CSR in India responds to monsoon shocks partially and with delay, with the response concentrated in poorer districts and operating mainly through drought.

Keywords: Corporate social responsibility, Mandatory CSR, Rainfall shocks, India, Development finance, Political economy

JEL: D72, M14, O12, Q54

Supervisor:	Abhijeet Singh
Date submitted:	18 May 2026
Date examined:	28 May 2026
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Acknowledgements

I would like to thank my supervisor, Abhijeet Singh, for his continuous support, valuable feedback, and patience throughout the entire writing process. I am also grateful to my family and friends for their useful comments and perspectives, especially in the final stretch of the writing process, as well as their encouragement throughout this process.

AI disclosure statement

In the process of writing this thesis, I have utilized artificial intelligence tools. More precisely, ChatGPT and Claude have assisted with coding and while Grammarly has served as a proofreading tool, correcting grammar and helping with structure. All AI outputs have been cautiously examined by me to make sure they are correct, fit their purposes and do not undermine the originality of my own work.

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1. Introduction

Governments across the developing world have increasingly pressed firms to contribute directly to social welfare, not merely as good corporate citizens, but in some cases as a matter of law. The Addis Ababa Action Agenda (2015) placed the private sector at the centre of the financing strategy for the Sustainable Development Goals, and cross-country evidence documents a broad expansion in corporate social responsibility (CSR) programmes since then (Kolk, 2016). Despite this policy ambition, whether corporate social spending reaches communities most in need, or simply flows toward places that are convenient for firms, remains an open question.

India provides a particularly useful setting to study this question. Section 135 of the Companies Act, 2013 requires large qualifying firms to spend at least two percent of average net profits each year on eligible CSR activities, covering areas such as health, education, and rural development. By 2023, aggregate expenditure under the mandate had reached approximately ₹350 billion (approximately USD 5 billion)[1]. Existing work shows that CSR spending is geographically concentrated in industrialised and urban districts and follows the geographic distribution of corporate activity far more closely than the distribution of poverty (Gawande and Pathak, 2024). Whether this pattern changes when districts face sudden adverse shocks is unknown. This paper asks whether mandated CSR spending reallocates geographically when Indian districts experience monsoon rainfall shocks.

Using a district-year panel covering 605 Indian districts from 2016 to 2023, the paper documents that national CSR spending rose substantially over the sample period but allocations remained dominated by a small number of industrial and metropolitan districts throughout. In cross-section, districts with higher poverty headcount ratios receive less CSR per capita, not more.

Year-to-year monsoon rainfall variation provides a plausibly exogenous source of local economic shocks across Indian districts, making it well suited to identify the effect of local conditions on CSR allocation. Adverse monsoon shocks are well documented to reduce agricultural wages, raise mortality, and heighten social stress in affected households, with effects concentrated in poorer and more agricultural districts (Jayachandran, 2006; Burgess et al., 2017; Sekhri and Storeygard, 2014). If CSR functions as a needs-responsive flow, spending should increase in shock-affected districts in the years following an adverse rainfall shock. If instead allocations remain governed by proximity to corporate activity and reputational considerations, little geographic reallocation should occur. To distinguish between these possibilities, the empirical strategy exploits within-district variation in rainfall over time, with district fixed effects

[1] All INR figures are in nominal terms. USD equivalents are approximate and use an exchange rate of INR 70.4 per USD, the annual average for 2019, the midpoint of the 2016–2023 sample period. Source: exchange-rates.org.

absorbing time-invariant district characteristics and year fixed effects absorbing aggregate trends and common shocks.

The analysis yields three findings. CSR spending does not respond to ordinary rainfall variation, and same-year responses to extreme shocks are not statistically significant in isolation. The main result is instead a delayed response. A drought is associated with approximately 11 to 14 percent higher CSR spending in the following year, a result that is robust across the main specifications. The corresponding excess-rain response is positive but smaller and not consistently significant. At two-year lags, excess-rain effects become significant while drought effects fade to marginal significance, suggesting that drought produces the strongest response at the one-year horizon and excess rainfall at two years. This timing is consistent with how India's CSR system operates in practice. Firm budgets are set annually, and project identification, partner selection, and disbursement typically take several months, making an immediate same-year response unlikely.

The lagged response is not uniform across districts. When CSR adjusts in response to rainfall shocks, the adjustment is concentrated in poorer districts rather than distributed evenly across affected areas, and the response is more strongly associated with district poverty than with agricultural dependence alone.

The paper also documents an independent association between state-assembly election timing and CSR allocation. State elections held in the second half of the year are associated with higher CSR spending regardless of rainfall conditions, consistent with firms directing resources toward politically salient districts ahead of competitive contests (Sinha et al., 2025). The lagged drought effect survives controls for election timing, indicating it reflects climatic responsiveness rather than political cycles.

This paper contributes to three strands of research. First, it extends the literature on India's mandatory CSR regime, which has focused on firm-level compliance and financial consequences of the mandate (Dharmapala and Khanna, 2018; Duggal et al., 2025; Altaf, 2023), but has not examined whether mandated spending responds to local shocks. This paper takes up that question directly using a district-year panel.

Second, it adds to the rainfall shock literature. Existing work documents that monsoon variation generates large welfare costs in rural India (Jayachandran, 2006; Burgess et al., 2017; Sekhri and Storeygard, 2014) but has not examined corporate spending as a response channel. This paper identifies mandatory CSR as a margin of adjustment to climatic shocks.

Third, it contributes to the literature on political incentives and CSR allocation. Work connecting corporate social spending to electoral cycles is concentrated in the United States and China (Bertrand et al., 2020), where institutional contexts differ substantially from India's mandatory CSR regime. Recent work on India by Sinha et al. (2025) documents election-year effects in mandated CSR. This paper adds climatic shocks to that frame, examining electoral and rainfall channels jointly in the Indian setting.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 describes India's CSR regulatory framework and the political economy of state elections. Section 4 presents the data and descriptive patterns. Section 5 sets out the empirical strategy and results. Section 6 concludes.

2. Literature Review

2.1 Conceptual foundations of CSR

Corporate social responsibility is most commonly understood through several complementary theoretical perspectives, each relevant to whether firms would adjust CSR spending when a local shock raises community need.

Stakeholder theory holds that firms operate within a network of relationships with employees, customers, suppliers, communities, governments, and investors, and that CSR is one mechanism through which firms maintain the cooperation of groups whose support is necessary for long-run viability (Freeman, 1984). Legitimacy theory offers a related perspective, holding that firms depend on a social licence to operate, maintained as long as their actions are perceived as appropriate within prevailing social norms (Suchman, 1995). When legitimacy is threatened by environmental damage, social conflict, or reputational pressure, firms may expand or redirect CSR to restore acceptance. Under both perspectives, some geographic responsiveness to shocks is plausible. If an adverse monsoon shock raises community needs sharply in a district where a firm operates, and this heightens stakeholder expectations or threatens local acceptance, firms would have reason to increase CSR toward that district.

Strategic CSR approaches treat social investment as part of competitive strategy. Porter and Kramer (2006) argue that firms create shared value by directing investment toward local conditions that strengthen their operating environment, such as infrastructure, workforce skills, and institutions in areas where they source labour or inputs. Under this view, firms with exposure to shock-affected districts through supply chains or local operations may have reason to respond, but firms whose activities are concentrated elsewhere would have little strategic incentive to redirect resources.

Each of these perspectives, however, also gives reason to expect spatial rigidity. Under stakeholder and legitimacy theories, the incentive to maintain relationships and protect reputation is strongest near a firm's existing operations, where monitoring is straightforward and stakeholder networks are already established. Under strategic approaches, investment flows toward the firm's existing competitive context rather than toward distant areas of need. In practice, the districts where these conditions hold, established industrial and urban centres, are not the districts where adverse shocks raise community needs. Which of these tendencies dominates is an empirical question.

2.2 CSR in development finance

CSR has been drawn into broader debates about development finance, particularly in the context of the Sustainable Development Goals. International frameworks increasingly present corporate social spending as complementary to official development assistance (ODA), and the Addis Ababa Action Agenda (2015) explicitly called on firms to help close the SDG financing gap. Blowfield and Frynas (2005) examined this framing critically and found that while businesses are routinely described as important actors in addressing poverty and welfare deficits, systematic evidence that CSR actually reaches those most in need remains limited.

The distinction between CSR and other categories of development finance, including ODA and private philanthropy, matters for understanding what to expect from India's mandatory CSR regime. ODA is allocated through public mandates and formal country strategies, with disbursement governed by agreed needs assessments and sector priorities. Large private foundations, though privately governed, tend to operate through defined sectoral priorities, and their grant-making is not primarily shaped by where donors conduct business (OECD, 2018). CSR differs from both in that firms retain considerable discretion over where to allocate resources, within the broad categories set out by regulation.

Positioned between corporate strategy and development policy, India's mandatory CSR regime is a useful test case for whether mandated corporate flows behave like a needs-responsive instrument or remain driven by the geography of existing corporate activity. It generates sizable and recurring flows that are formally framed as development-oriented, but unlike ODA and private philanthropy, its allocation is not governed by any centralised needs-assessment system. It operates under a legal mandate with reporting obligations, but allocation decisions remain at corporate discretion. Whether CSR spending responds to local needs despite the absence of formal geographic targeting in the regulatory framework is the empirical question this paper addresses.

2.3 Determinants and spatial allocation of CSR in India

The introduction of Section 135 in 2013 substantially increased CSR activity among eligible firms. Dharmapala and Khanna (2018) compare firms just above and just below the statutory eligibility thresholds and find a real increase in spending among those that crossed into obligation, driven more by firms newly initiating CSR than by existing spenders scaling up their budgets. They also document substitution away from advertising expenditure, consistent with firms using CSR partly as a signalling tool, a form of reputational investment rather than a direct response to community need. Subsequent work reinforces this interpretation. Duggal et al. (2025) find that firms complying with the mandate face lower borrowing costs, suggesting that lenders treat CSR compliance as a signal of governance quality. Altaf (2023) links CSR engagement to higher cash holdings and greater trade-credit extension, pointing to connections between CSR activity, trust-based business relationships, and liquidity management.

These findings have a direct implication for where CSR flows. If firms use CSR partly for signalling and relationship investment, allocations will cluster where monitoring is easy, stakeholders are visible, and reputational returns are highest, which in practice means near existing corporate activity. The data confirm this at every spatial scale. Gawande and Pathak (2024) show that economically stronger states receive disproportionately larger CSR inflows while poorer and less industrialised regions are consistently underfunded, and the same pattern holds within states, where districts with stronger industrial and urban footprints receive substantially more than low-income, predominantly rural ones. Assessments from KPMG (2018) and CSRBOX (2024) find spending concentrated in major industrial clusters in Maharashtra, Gujarat, Karnataka, and Tamil Nadu, with allocations to aspirational and backward districts well below their population shares.

A related body of work examines whether political incentives shape CSR allocation and broader resource responses to local conditions. In the United States, Bertrand et al. (2020) show that corporate donations by large firms are directed in part toward legislators with political influence, paralleling the strategic use of campaign spending. Besley and Burgess (2002) establish a broader pattern in the Indian context. Using panel data on Indian states, they show that state governments allocate more public food distribution and calamity relief expenditure in response to falls in food production and flood damage where electoral accountability is higher, demonstrating that electoral incentives shape the geographic distribution of resource responses to agricultural shocks in India. More directly, Sinha et al. (2025) use the staggered timing of Indian state elections to show that districts receive significantly more CSR spending in election years, with increases concentrated in districts represented by majority-party incumbents and in project categories with high voter visibility such as health, education, and employment. Tarquinio (2023) provides complementary evidence from the public sector side, showing that state governments in southern India systematically deviate from national guidelines when allocating drought relief, redirecting resources based on electoral competition motives rather than drought severity. These findings suggest that political considerations independently shape where resources flow in response to agricultural shocks in India.

Taken together, the evidence suggests that CSR allocation under the mandatory regime is shaped primarily by corporate geography, firm-level incentives, and political timing rather than by community need. What this literature has not examined is whether allocation patterns change when particular districts experience sudden adverse shocks, and whether any such response is distinct from the politically driven cycles that recent work documents.

2.4 Rainfall shocks and local economic distress in India

Rainfall shocks in India provide a widely used source of plausibly exogenous variation in local economic conditions. Because large parts of rural India remain heavily dependent on monsoon rainfall, deviations from long-run district averages generate substantial fluctuations in agricultural output, wages, and household welfare.

Jayachandran (2006) shows that negative rainfall shocks depress rural wages by reducing labour demand while credit-constrained workers are forced to increase labour supply, with the largest effects in poorer districts with thinner financial markets. Burgess et al. (2017) show that hot days substantially increase mortality in rural India, with effects concentrated in the agricultural growing season. The mechanism runs through income, as heat depresses agricultural yields and wages, leaving credit-constrained households with fewer resources to spend on health goods. Shah and Steinberg (2017) show that positive rainfall shocks reduce human capital investment in rural India by raising agricultural wages and increasing the opportunity cost of schooling, so that children switch out of school into productive work. Sekhri and Storeygard (2014) show that drought shocks are associated with higher rates of dowry deaths, which they interpret as evidence that income declines lead to economically motivated demands on household resources, illustrating that the welfare costs of monsoon shocks extend beyond income into social outcomes.

Existing coping mechanisms provide only partial relief. Informal risk-sharing works reasonably well for idiosyncratic shocks but breaks down when shocks are geographically widespread and affect entire communities simultaneously (Townsend, 1994). Seasonal migration is most costly for credit-constrained households (Jayachandran, 2006). India's rural employment guarantee scheme (MGNREGA), while providing a public safety net, covers neither all affected households nor all dimensions of welfare loss. These gaps leave substantial unmet need in the aftermath of adverse monsoon shocks. The districts most affected are precisely the poorer and more agricultural ones that CSR currently underserves, making rainfall shocks a natural test of whether mandated corporate spending responds to rising local need.

The literatures on CSR allocation in India and on the welfare costs of rainfall shocks have not yet been connected. CSR research has not asked whether mandated spending responds to local shocks, and the rainfall shock literature has not examined corporate spending as a response channel. This paper brings them together by asking whether district-level CSR allocations adjust to adverse monsoon shocks, using within-district rainfall variation to identify the response.

3. Institutional and Regulatory Context

India is a federal republic comprising 28 states and 8 union territories. Each state and union territory is divided into districts, which serve as the principal administrative unit for local governance, development planning, and the collection and reporting of economic and social data.

3.1 The Indian CSR Framework

India is widely recognised as the first country to require large firms to spend a fixed share of profits on CSR activities directly. Section 135 of the Companies Act, 2013 requires companies above specified size thresholds, based on net worth, turnover, or net profit, to constitute a CSR Committee of the Board and undertake CSR activities in accordance with a formally adopted CSR policy. Eligible firms must spend at least 2% of average net profits over the three preceding financial years on CSR activities each year. If the prescribed amount is not spent, the Board must disclose the reasons in its annual report, and following subsequent amendments, unspent funds must be transferred either to a designated government fund or to a special unspent CSR account within prescribed timelines.

The operational details are set out in the Companies (Corporate Social Responsibility Policy) Rules, 2014, as amended. The Rules require firms to articulate a written policy specifying the activities to be undertaken, modalities of implementation, and monitoring arrangements. They also specify that CSR cannot include activities undertaken in the ordinary course of business, projects that benefit only employees, or contributions to political parties. Firms may implement CSR projects directly, through corporate foundations, or through registered implementing agencies. Amendments to the Rules have introduced additional compliance measures, including impact assessments for large CSR programmes and stricter rules governing the treatment and disclosure of unspent amounts. Non-compliance with these requirements can attract penalties under the Act, though in practice enforcement has operated primarily through mandatory disclosure rather than direct sanctions.

The scope of eligible activities is defined in Schedule VII of the Companies Act, 2013, which groups them into broad development-focused categories: reducing hunger and poverty, improving healthcare and sanitation, expanding access to education and skill development, promoting gender equality, supporting environmental sustainability, advancing rural development, and undertaking disaster management and rehabilitation. The broad wording of Schedule VII gives firms considerable discretion in project selection. The framework specifies what firms may spend on but does not include geographic allocation criteria, leaving allocation decisions largely at corporate discretion.

Section 135, the CSR Rules, and Schedule VII together establish a regulatory framework in which large firms are legally obliged to allocate resources to broadly defined development activities, with increasing emphasis on compliance and transparency. The absence of geographic targeting requirements means that allocation is determined by corporate choices rather than regulatory design, which motivates the empirical analysis in Sections 4 and 5.

3.2 Reporting, monitoring, and data limitations

India's CSR framework is fundamentally disclosure-based. The government monitors compliance through company filings, including annual reports and CSR-specific disclosures submitted via the MCA-21 system (Ministry of Corporate Affairs, 2021). From 2022, companies must also file Form CSR-2, a detailed report on CSR activities, expenditure, and committee composition (Companies (Accounts) Amendment Rules, 2022). These reforms have aimed to standardise reporting, but the system remains heavily reliant on self-reported information from firms, and the government's own CSR data portal notes that it cannot guarantee the completeness or accuracy of the data it publishes (Ministry of Corporate Affairs, National CSR Portal).

Mandatory reporting does not guarantee accurate measurement. The Parliamentary Standing Committee on Finance found that information on CSR spending is insufficient and called for third-party audits of CSR funds, a recommendation the Ministry declined on the grounds that existing provisions provide adequate safeguards (Parliamentary Standing Committee on Finance, 2022). Independent audit of CSR activities is not mandatory under the Companies Act, 2013, and verification of reported activities remains limited. These are reporting and verification limitations rather than evidence of systematic misreporting, but they imply that CSR expenditure data may not fully capture the extent or quality of on-the-ground implementation. The empirical analysis therefore uses reported CSR expenditure as the outcome variable, examining where funds are directed across districts rather than how they are used on the ground.

3.3 Political economy of state elections and CSR

India's state legislative assemblies, the Vidhan Sabha, are directly elected through a first-past-the-post system from single-member constituencies and serve five-year terms, subject to early dissolution. Elections are held on different schedules across states rather than simultaneously, so in any given year some states are in an election year while others are not. Incumbent state governments have electoral incentives to encourage visible private spending in their jurisdictions ahead of competitive contests, and firms with established operations in a state may direct CSR toward politically salient projects or districts to maintain relationships with state-level governments (Sinha et al., 2025). Because election timing is independent of rainfall, election-year effects can be examined separately from the rainfall response. Section 5.4 addresses this directly.

4. Data and Descriptive Patterns

4.1 Data sources

This study combines company-level CSR disclosures, rainfall data, and socioeconomic indicators, all matched to 2011 district boundaries. CSR data come from Dataful (Factly), which compiles firms' CSR filings under Section 135 of the Companies Act, 2013; state-year totals were spot-checked against the National CSR Data Portal to verify reliability. Rainfall data are from CHIRPS v3.0 (0.05° daily resolution), aggregated to the June–September monsoon (JJAS) for each district and year.

Socioeconomic indicators, including literacy, agricultural workforce share, urban share, and 2011 population baselines, are from the Census of India (2011) Primary Census Abstract. Population for 2016–2023 is projected from 2011 levels using state-specific growth rates from the National Commission on Population (2020). Poverty data are taken from the Global Multidimensional Poverty Index (MPI) 2018 published by OPHI and UNDP. Election timing data come from the Trivedi Centre for Political Data (TCPD), Ashoka University. District area and identifiers follow the 2011 Census Administrative Atlas. The 2011 Census shapefile contains 640 districts. Of these, 605 form the matched panel used in the analysis. The remaining 35 are excluded due to district splits and boundary changes between 2011 and 2023, or to missing reporting in the underlying source.

4.1.1 Final dataset and variable construction

The dataset forms a balanced panel of 605 districts observed annually from 2016 to 2023, yielding 4,840 district–year observations.

The main dependent variable is the logarithm of total CSR spending, $log(1 + CSR_{i}\square)$, measured in nominal INR. This transformation reduces skewness and accommodates districts with zero CSR spending.[2] CSR per capita is not used as the primary outcome as district populations range from under 100,000 to over 12 million, and population projections from the 2011 Census introduce measurement error in the denominator that compounds across the panel, making per-capita values less reliable, particularly for smaller districts.

JJAS covers June through September, India's core monsoon season and the primary window for rain-fed agriculture. Monsoon rainfall totals (millimetres) are derived from CHIRPS v3.0 by aggregating daily data over JJAS for each district. Three rainfall indicators are used. The continuous standardised rainfall deviation is defined as

$$rain_{z,it} = \frac{JJAS_{it} - \overline{JJAS_i}}{sd(JJAS_i)}$$

where the mean and standard deviation are computed over 2016–2023 for each district.

Standardisation within the 2016–2023 window rather than against a longer historical baseline interprets shocks as deviations from each district's recent climate. This is the relevant benchmark for short-run economic responses because local agricultural systems and labour markets are adapted to district climatology. By construction, the mean shock across the panel is zero and the pooled standard deviation is approximately one, preventing long-run climate trends from driving identification.

Two binary indicators capture threshold events: a district-year is classified as drought if $rain\_z \leq -1$ and as excess rain if $rain\_z \geq +1$. The ±1 standard deviation thresholds mark moderate negative or positive deviations and are used to distinguish threshold responses from linear rainfall effects.

The main control variable is log population, projected from 2011 Census baselines using state-specific growth rates. District characteristics used in heterogeneity analysis include literacy rate, MPI poverty headcount, urban share, and agricultural workforce share (defined as cultivators plus agricultural labourers as a share of total workers). An election-year indicator

[2] Between one and ten districts record zero CSR spending in any given year; the log(1 + CSR) transformation retains these observations in the panel.

equal to one in years when district *i*'s state holds a state-assembly election is included in Section 5.4, along with pre-election and post-election indicators equal to one in the years immediately preceding and following the election. Early election years are state assembly elections held in January through June; late election years are elections held in July through December, based on the month of polling as recorded in the TCPD data.

Table 1 reports summary statistics for the main variables. The panel covers a wide range of district conditions, from highly urbanised, service-oriented areas to predominantly agrarian regions, and rainfall variation is broadly balanced around normal levels over time[3].

Table 1. Descriptive statistics

Variable	n	Mean	SD	Min	p10	Median	p90	Max
CSR spending (INR millions)	4825	127.01	837.00	0.00	0.00	10.30	218.00	29802.00
CSR per capita (INR)	4825	50.20	255.00	0.00	0.00	5.89	111.00	8639.00
Population (millions)	4840	2.10	1.73	0.01	0.30	1.72	4.27	12.56
Rainfall shock (z-score)	4840	0.00	0.94	-2.30	-1.16	-0.08	1.34	2.37
MPI headcount (%)	4840	35.64	11.44	8.83	19.87	36.10	49.77	62.80
Literacy rate (%, 2011)	4840	72.28	10.52	36.10	58.82	72.17	85.44	97.91
Urban share (%, 2011)	4840	25.93	20.35	0.00	7.18	19.82	54.76	100.00
Agricultural workforce share (%, 2011)	4840	57.14	20.69	0.00	24.65	62.46	79.47	89.99
District area (km^2)	4840	4936.02	5164.08	9.85	1430.56	3794.69	9241.52	80274.39
Population density (per km^2)	4840	1006.62	4018.42	1.14	114.58	414.21	1325.62	57112.26

Notes: The sample is a balanced district–year panel of 605 Indian districts, 2016–2023 (4,840 observations). CSR spending is expressed in INR millions; CSR per capita in INR per person. Population is in the millions. Rainfall shock is the standardised JJAS monsoon deviation, computed within each district over 2016–2023. MPI headcount is the share of the district population classified as multidimensionally poor (Global MPI 2018). Shares and rates are expressed as percentages. CSR variables have 4,825 observations due to 15 missing values in the source data. Source: Dataful (Factly); CHIRPS v3.0 (Funk et al., 2015); Global MPI 2018 (OPHI/UNDP); Census of India (2011).

[3] Aggregate national totals shown in Figure 1 include CSR not attributable to specific districts; the district-year panel captures the subset of CSR explicitly assigned to a district at the time of filing.

4.2 Descriptive results

Total CSR spending rose from approximately ₹153 billion (USD 2.2 billion) in 2016 to approximately ₹350 billion (USD 5.0 billion) in 2023. The sharpest year-on-year increase occurred between 2018 and 2019, with continued growth into 2020 that coincided with regulatory changes expanding eligible CSR activities to include COVID-19 relief spending (Ministry of Corporate Affairs, General Circular No. 10/2020) and tightening compliance requirements for unspent CSR amounts (Companies (Amendment) Act, 2020). Spending then declined modestly in 2021 before rising again in 2022 and 2023, producing a substantial but non-monotonic upward trend over the period.

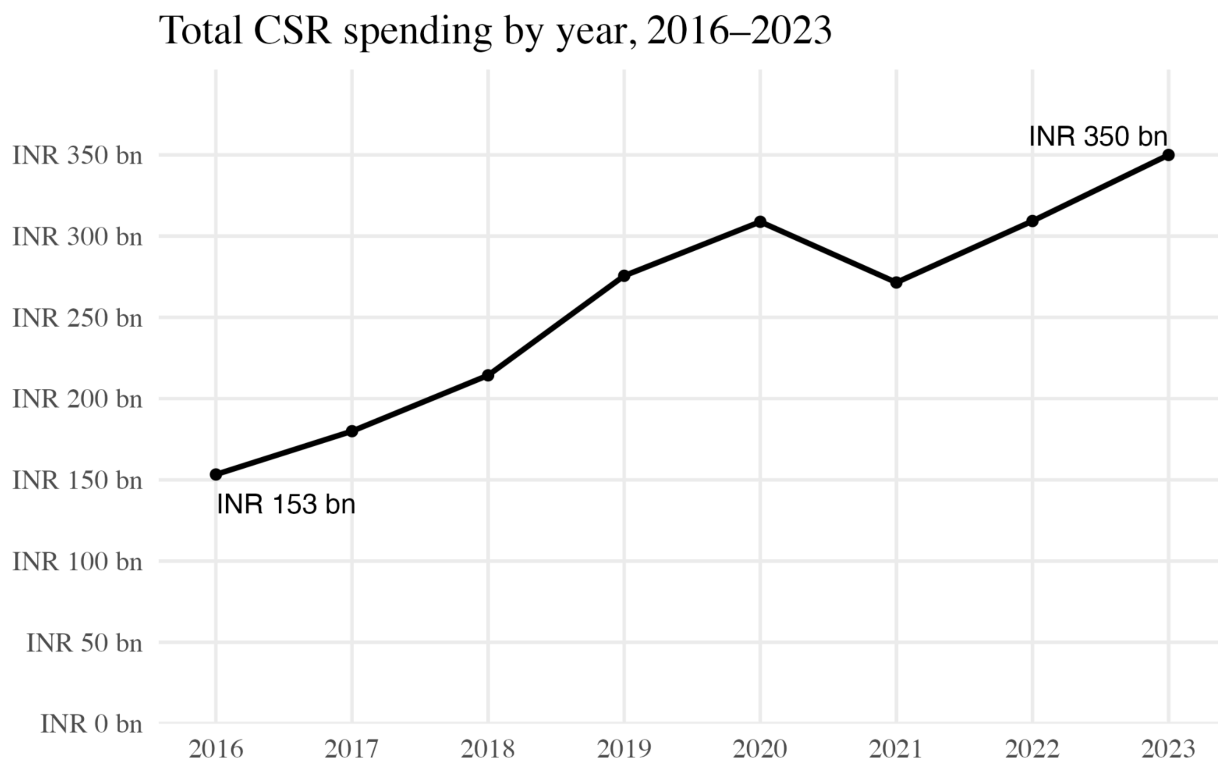

Figure 1. Total CSR spending by year, 2016–2023

Notes: Total reported CSR expenditure by year, 2016–2023. Values in nominal INR.

Source: Author's rendering of Dataful (Factly) data (2016–2023).

CSR allocations rose in most major recipient states between 2016 and 2023, though the distribution remained highly unequal. The largest recipient state in 2023 was Maharashtra, at approximately ₹60.7 billion (USD 862 million), followed by Gujarat, Karnataka, Tamil Nadu, Delhi, and Uttar Pradesh, which received between roughly ₹15.5 and ₹27.1 billion (USD 220–385 million). Together with four other high-spending states, the top ten recipients accounted for 75.7% of national CSR allocations in 2023. At the other end of the distribution, territories and smaller states such as Lakshadweep, Andaman and Nicobar Islands, Mizoram, Tripura, Daman and Diu, and Dadra and Nagar Haveli remained below ₹0.2 billion (USD 3 million) throughout the period. Median state-level CSR spending rose from about ₹1.0 billion (USD 14 million) in 2016 to ₹3.7 billion (USD 53 million) in 2023. The 90th-to-10th-percentile ratio of state CSR spending declined from about 699:1 in 2016 to roughly 246:1 in 2023, indicating that inequality across states remained very large, though somewhat less extreme than at the start of the period.

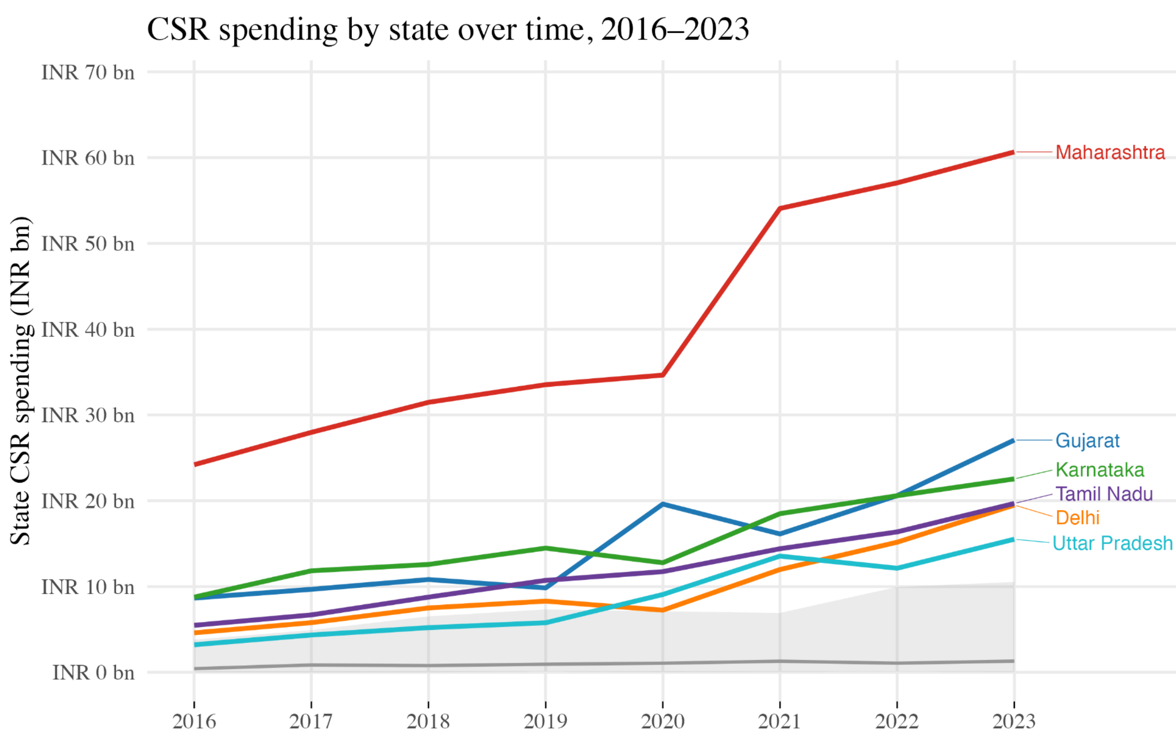

Figure 2. CSR spending by state over time, 2016–2023

Notes: Total reported CSR expenditure by state, 2016–2023. Top six states by 2023 level are highlighted. The grey band shows the 10th–90th percentile range across all other states, with the solid grey line showing their median. Values in nominal INR.

Source: Author's rendering of Dataful (Factly) data (2016–2023).

The geographic reach of spending widened over time. The number of districts reporting zero CSR ranged from 5 to 11 in the early years and fell to almost none by 2023. Despite this near-universal coverage, spending remains highly concentrated. A small group of industrial and metropolitan districts accounts for a disproportionate share of total spending, while most of central and eastern India receives comparatively modest inflows. Districts with the largest allocations are concentrated in major industrial and metropolitan regions, including Delhi, the Mumbai–Thane–Pune corridor, Ahmedabad–Surat, Bengaluru, Hyderabad, and Chennai, as well as in the eastern mining belts of Odisha, Jharkhand, and Chhattisgarh.

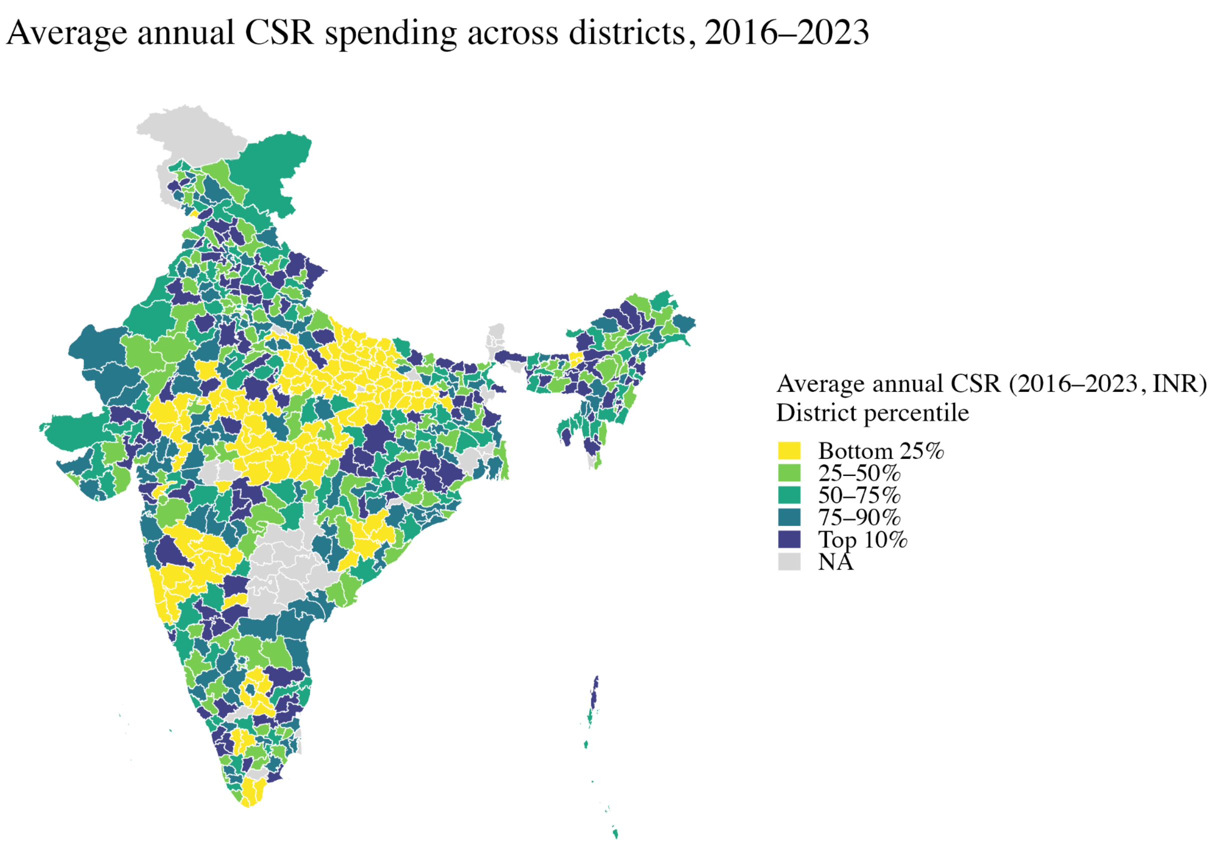

Figure 3. Average annual CSR spending across districts, 2016–2023
Notes: Districts are ranked by average annual CSR expenditure (2016–2023) and grouped into five percentile bands. Grey areas indicate 2011 districts not included in the final matched panel.
Source: Author's rendering of Dataful (Factly) and Census of India (2011) data (2016–2023).

Raw CSR spending is highly right-skewed, with most district-years receiving modest amounts and a long upper tail of large allocations. This motivates the logarithmic transformation used in the empirical analysis. Figure 4 shows the resulting log distribution, with most mass concentrated in the upper-middle range and a small spike at zero corresponding to district-years with no CSR spending.

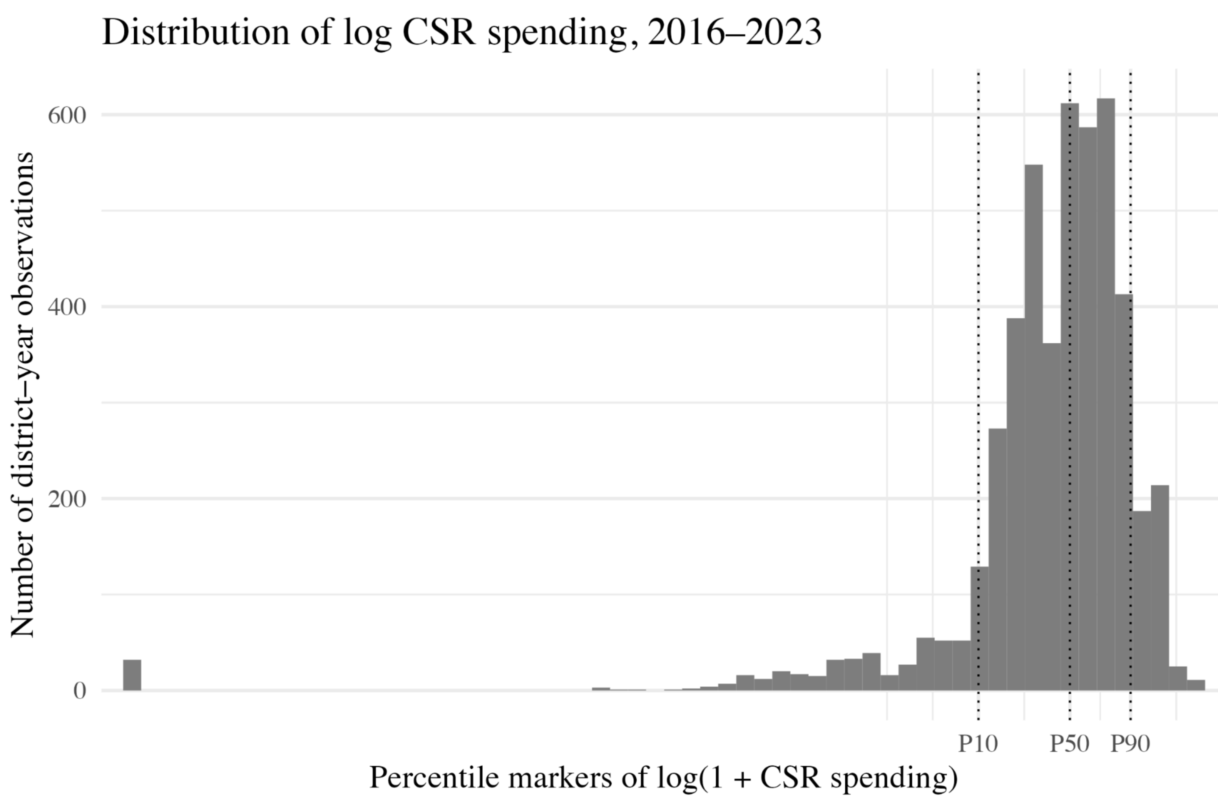

Figure 4. Distribution of log CSR spending, 2016–2023

Notes: Distribution of log(1 + CSR spending) across district–year observations (605 districts, 2016–2023), trimmed at the 99.5th percentile. Vertical dotted lines mark the 10th, 50th, and 90th percentiles of the trimmed distribution.

Source: Author's rendering of Dataful (Factly) data (2016–2023).

In cross-section, both total CSR spending and CSR per capita are negatively associated with district poverty levels, with higher MPI headcount ratios associated with lower CSR allocations, consistent with the geographic concentration patterns described above and with the evidence reviewed in Section 2.3.

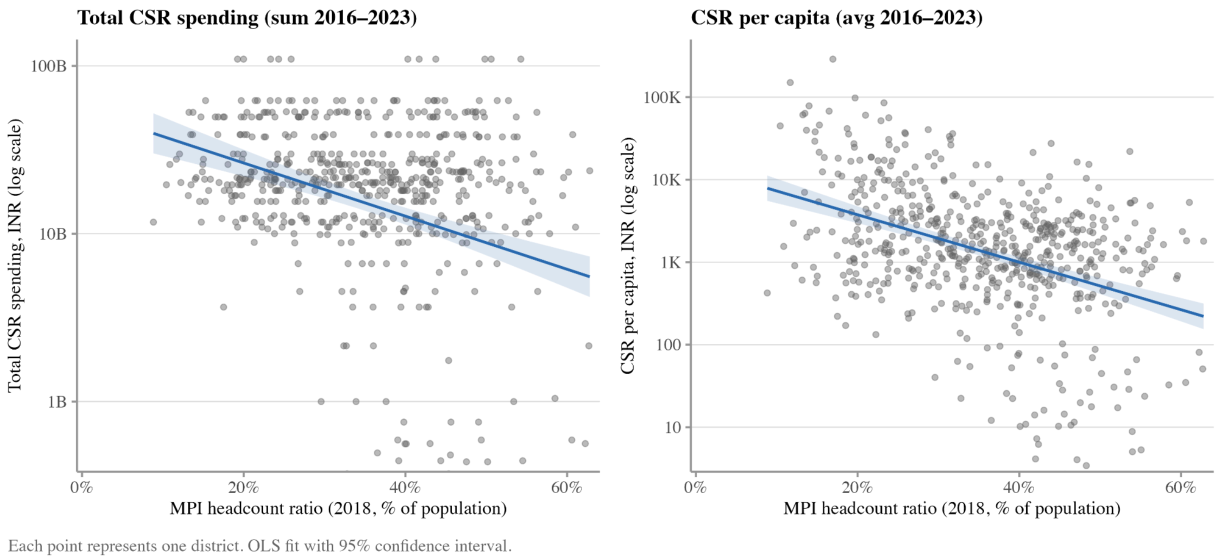

Figure 5. Total CSR spending versus MPI poverty headcount

Notes: Each point represents one district. The left panel shows total CSR spending summed over 2016–2023; the right panel shows CSR per capita averaged over 2016–2023. The x-axis shows the MPI poverty headcount (2018), the share of the district population classified as multidimensionally poor across health, education, and living standards dimensions. Both y-axes are on a log scale. The fitted line shows an OLS regression with a 95% confidence interval.

Source: Author's rendering of Dataful (Factly) and Global MPI 2018 (OPHI/UNDP) data (2016–2023), including OLS regression fit with 95% confidence interval.

Rainfall shocks, measured through district-level deviations from the district mean, vary substantially across space and time. There is no persistent national trend, but there are strong regional fluctuations from year to year. Maps for four example years illustrate how dry and wet conditions shift across India. In 2016, below-average rainfall dominated much of southern and western India. In 2018, wetter conditions appear across northern and northeastern states. The year 2020 records widespread positive rainfall across central and southern areas, while deficits persist in the northwest. In 2022, below-average deviations re-emerge in central and western districts. Across the selected years shown in Figure 6, national rainfall deviations fluctuate around the mean, from roughly −0.18σ in 2022 to +0.23σ in 2020. Across years, approximately 8–28% of districts experience drought conditions ($rain\_z \leq -1$) and 6–26% record excess rainfall

($rain\_z \geq +1$), providing sufficient within-sample variation to identify responses to both types of shock.

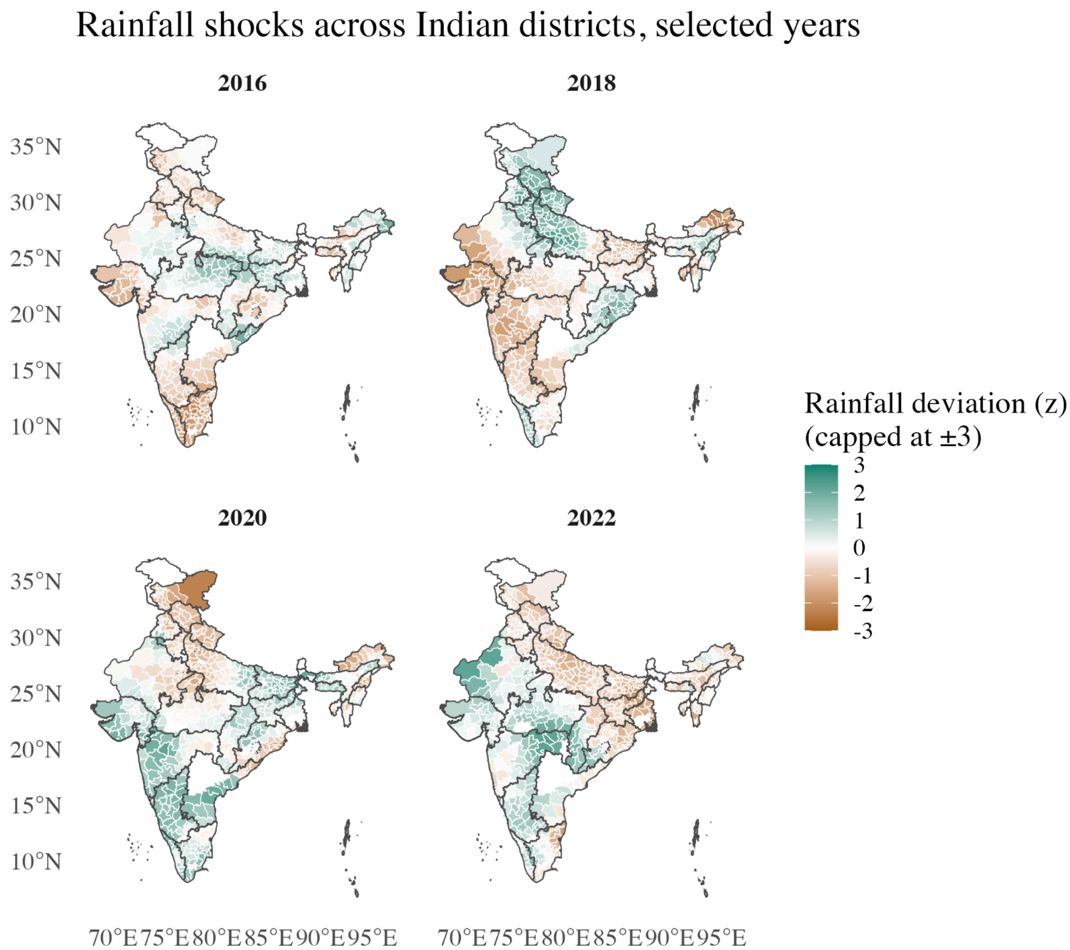

Figure 6. Rainfall shocks across Indian districts, selected years

Notes: District-level monsoon rainfall deviations (rain_z) for 2016, 2018, 2020, and 2022. rain_z is standardised relative to each district's 2016–2023 mean. The colour scale is capped at ±3 standard deviations. Grey areas indicate unmatched districts.

Source: Author's rendering of CHIRPS Version 3.0 (Funk et al., 2015) and Census of India (2011) data.

At the state level, annual mean monsoon deviations oscillate around zero throughout the period, with no systematic trend. The national mean is slightly positive in 2018–2019 (peaking near +0.3σ) and below normal in 2022–2023 (around −0.4σ). Dispersion is particularly wide in 2018, with the gap between the driest and wettest states exceeding three standard deviations. Across 2016–2023, states differ substantially in the frequency of below- and above-average monsoon years, showing the idiosyncratic nature of rainfall shocks across India.

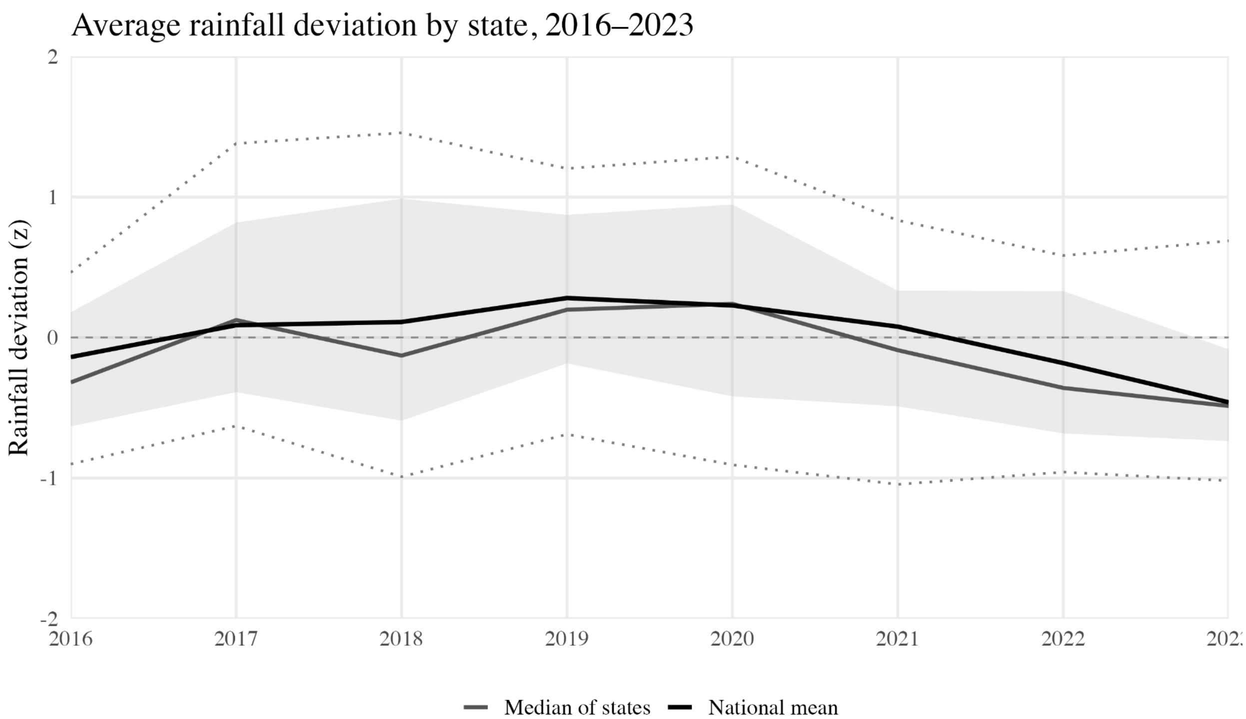

Figure 7. Average rainfall deviation by state, 2016–2023

Notes: Annual mean monsoon rainfall deviation (rain_z) by state, 2016–2023. The shaded band shows the interquartile range (25th–75th percentile) across states. Dotted lines show the 10th and 90th percentiles. The solid grey line is the median of states and the solid black line is the national mean.

Source: Author's rendering of CHIRPS Version 3.0 (Funk et al., 2015) data (2016–2023).

Three features of the descriptive evidence stand out. CSR spending expanded substantially over the sample period but remains geographically concentrated in industrial and metropolitan districts. In cross-section, districts with higher poverty receive less CSR, not more. Rainfall shocks vary substantially across districts and years without following a systematic trend. These allocation patterns mean that evidence of CSR reallocation toward shock-affected districts would represent a departure from existing patterns. The absence of systematic rainfall trends supports the use of within-district variation as a source of identification in Section 5, as year-to-year shocks are not confounded by long-run drying or wetting trends.

5. Empirical Strategy and Results

5.1 Empirical strategy

The baseline specification relates log CSR spending in district *i* and year *t* to within-district variation in monsoon rainfall:

$$log(1 + CSR_{it}) = \beta \cdot Shock_{it} + \gamma \cdot log(Population_{it}) + \alpha_i + \delta_t + \varepsilon_{it}$$

where $log(1 + CSR_{it})$ is the logarithm of total district-year CSR expenditure, transformed to reduce skewness and retain districts with zero spending. Shock_{it} is either the continuous standardised rainfall deviation or the binary drought and excess-rain indicators defined in Section 4. District fixed effects (α_i) absorb time-invariant characteristics including geography, industrial composition, and persistent differences in corporate presence. Year fixed effects (δ_{it}) capture aggregate trends and common shocks. Standard errors are clustered at the district level throughout[4].

For the heterogeneity analysis in Section 5.3, the specification extends to include interactions between one-year-lagged shocks and standardised district characteristics:

$$log(1 + CSR_{it}) = \beta_1 Drought_{i,t-1} + \beta_2(Drought_{i,t-1} \times Z_i) + \beta_3 Excess_{i,t-1} + \beta_4(Excess_{i,t-1} \times Z_i) + \gamma log(Population_{it}) + \alpha_i + \delta_t + \varepsilon_{it}$$

where Z_i is a time-invariant district characteristic, standardised to have mean zero and unit standard deviation. It is alternately defined as the agricultural workforce share from the 2011 Census or the multidimensional poverty headcount from the 2018 MPI. The coefficient β_1

[4] CSR is measured in nominal INR, so the additive constant in log(1 + CSR) is negligible relative to typical values and the coefficient β admits the standard semi-elasticity interpretation. Chen and Roth (2024) show that log(1 + y) coefficients can be sensitive to the units of y when zero values are present. The unit-sensitivity is minimal in this setting because non-zero CSR observations are several orders of magnitude larger than one rupee.

captures the lagged drought response at the mean of Z_i, while β_2 captures how this response changes with a one-standard-deviation increase in the moderator.

The identifying assumption is that year-to-year monsoon variation is uncorrelated with unobserved determinants of CSR allocation within districts, conditional on district and year fixed effects. Rainfall shocks influence CSR allocation through multiple channels. Firms may respond to local distress directly through their existing operations and stakeholder networks, or indirectly through state-government drought and flood declarations that activate relief programmes (Disaster Management Act, 2005). These channels are mechanisms through which the rainfall shock operates, not confounders. Each is itself a consequence of the same plausibly exogenous monsoon variation. The estimates therefore capture the combined response of CSR to rainfall shocks, including responses mediated by state-level action. A placebo test using one-year-ahead leads of the rainfall shock finds no evidence of anticipatory responses (Appendix Table A1), consistent with the identifying assumption. When year fixed effects are replaced with state-by-year fixed effects, the lagged drought coefficient loses significance and the lagged excess-rain result survives (Appendix Table A2). This pattern reflects the spatial correlation of drought within states. State-by-year fixed effects absorb most of the variation in the drought indicator, leaving little within-state variation for identification.[5]

[5] Approximately 60 percent of state-year cells contain zero within-state drought variation, and the average within-state-year standard deviation of the drought indicator is 0.17, less than half the pooled standard deviation of 0.36.

5.2 Baseline and timing results

Table 2. Baseline and timing results

	Dependent variable: log(1 + CSR spending)				
	(1)	(2)	(3)	(4)	(5)
Rain deviation (z)	-0.008				
	(0.019)				
Drought (t)		0.079		0.120*	0.189***
		(0.059)		(0.070)	(0.051)
Excess rain (t)		0.075		0.130**	0.165**
		(0.061)		(0.064)	(0.078)
Drought (t-1)			0.105**	0.128***	0.120**
			(0.041)	(0.047)	(0.058)
Excess rain (t-1)			0.081	0.098*	0.095
			(0.055)	(0.059)	(0.063)
Drought (t-2)					0.074*
					(0.042)
Excess rain (t-2)					0.140**
					(0.060)
Log population	2.354**	2.369**	3.657**	3.735**	3.714***
	(1.143)	(1.130)	(1.664)	(1.688)	(1.421)
Observations	4825	4825	4220	4220	3615
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.001	0.002	0.003	0.005	0.01

Notes: Column (1) reports the baseline model with the continuous rainfall deviation. Column (2) replaces the deviation with same-year drought and excess-rain indicators. Column (3) uses one-year-lagged drought and excess-rain indicators. Column (4) includes both contemporaneous and lagged shock indicators. Column (5) adds two-year lags to test persistence. Lagged shock indicators remain missing when lag history is unavailable. All models include district and year fixed effects. Standard errors clustered at the district level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2 reports the baseline specifications, varying the timing of the rainfall shock. The continuous rainfall deviation measure in column (1) has a small, statistically insignificant coefficient of −0.008, indicating no systematic linear relationship between ordinary rainfall deviations and CSR spending. Column (2) estimates same-year drought and excess-rain indicators separately, without lags. Neither is statistically significant in this standalone specification, suggesting no detectable same-year response when contemporaneous effects are estimated in isolation.

The main result emerges once lagged shocks are introduced. In column (3), the one-year lagged drought indicator is positive and statistically significant at 0.105, implying approximately 11 percent higher CSR spending in the year following a drought. Lagged excess rainfall is positive but not statistically significant in this column.

Column (4) includes both contemporaneous and lagged indicators jointly. The lagged drought coefficient rises to 0.128 and remains significant at the 1 percent level. When estimated jointly with lags, the contemporaneous drought indicator becomes marginally significant at 0.120 and contemporaneous excess rain is significant at 0.130, results that did not appear when contemporaneous indicators were estimated without lags in column (2). Lagged excess rain is marginally significant at 0.098 in this specification, though this does not persist across all columns. Column (5) adds two-year lags. The two-year-lagged drought coefficient is marginally significant at 0.074, and two-year-lagged excess rain is significant at 0.140, suggesting the response to rainfall shocks does not fully dissipate within one year. The one-year lagged drought effect remains the most stable and precisely estimated finding across all specifications, consistent with evidence that negative monsoon shocks produce substantially larger agricultural yield losses than positive shocks in India (Brey and Hertweck, 2023).

Across columns, the pattern points to a delayed rather than contemporaneous response. Same-year effects are absent when shock indicators are estimated in isolation, but some contemporaneous effects emerge when estimated jointly with lags. This timing is consistent with how India's CSR system operates. Firm budgets are set annually, and project identification, partner selection, and disbursement typically take several months, making an immediate same-year response unlikely. This mechanism cannot be directly tested with the available data.

When the analysis is repeated using log CSR per capita, the lagged drought coefficient is near zero and statistically insignificant (Appendix Table A3). This is an important limitation. The main estimates indicate an increase in total CSR flows to drought-affected districts, but the per-capita specification does not establish whether spending increased per resident. The null persists even after excluding the smallest 5 percent of districts (Appendix Table A4), so the divergence is not driven solely by measurement error in the denominator. Disentangling whether the response operates through a small number of large project allocations or a broader rise in per-resident funding would require firm- and project-level data. A complementary Poisson pseudo-maximum-likelihood specification, which models CSR in levels and addresses the Chen and Roth (2024) concern about *log(1 + CSR)* coefficients with zero observations, also yields a small and insignificant lagged drought coefficient (Appendix Table A5). Together with the per-capita null, this indicates that the lagged response observed in the log specification does not translate into a comparable shift in aggregate CSR mass.

5.3 Heterogeneity by agricultural dependence and poverty

Table 3. Heterogeneity in the lagged CSR response

	Dependent variable: log(1 + CSR spending)		
	(1)	(2)	(3)
Drought (t-1)	0.108***	0.110***	0.110***
	(0.041)	(0.041)	(0.042)
Excess rain (t-1)	0.079	0.073	0.073
	(0.054)	(0.052)	(0.052)
Drought (t-1) × Agriculture (z)	0.081**		0.013
	(0.032)		(0.030)
Excess rain (t-1) × Agriculture (z)	0.055		-0.023
	(0.039)		(0.040)
Drought (t-1) × Poverty (MPI z)		0.125***	0.118***
		(0.039)	(0.041)
Excess rain (t-1) × Poverty (MPI z)		0.116***	0.130***
		(0.045)	(0.048)
Log population	3.623**	3.632**	3.601**
	(1.710)	(1.701)	(1.701)
Observations	4220	4220	4220
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Within R-squared	0.003	0.005	0.005

Notes: All columns use one-year-lagged drought and excess-rain indicators. Column (1) tests whether the lagged CSR response differs with agricultural dependence. Column (2) tests whether the lagged CSR response differs with district poverty. Column (3) includes both interaction channels jointly. Agriculture and poverty variables are standardised (mean 0, standard deviation 1). All models include district and year fixed effects. Standard errors clustered at the district level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 examines whether the lagged response to rainfall shocks varies with district characteristics. All specifications use the one-year lagged framework from the baseline.

Column (1) interacts lagged drought and excess-rain indicators with the standardised agricultural workforce share. The drought interaction is positive and significant at 0.081, indicating that the lagged CSR response is larger in more agricultural districts. The excess-rain interaction is positive but not significant.

Column (2) interacts lagged shocks with the standardised MPI poverty headcount. Both the drought interaction at 0.125 and the excess-rain interaction at 0.116 are positive and highly significant, indicating that CSR responses after both types of shock are concentrated in poorer districts. The excess-rain poverty interaction is notable as it is significant and large across both columns (2) and (3), suggesting that the response to excess rainfall shocks is also directed toward areas of higher deprivation rather than distributed uniformly.

Column (3) includes both sets of interactions jointly. The poverty interactions remain large and statistically significant, while the agriculture interactions lose significance and become small. At one standard deviation above mean MPI headcount, the lagged drought response rises to approximately 26 percent higher CSR spending, roughly twice the average. The results suggest that the lagged CSR response is therefore more strongly associated with multidimensional poverty than with agricultural dependence alone.

5.4 Political cycles and CSR allocation

Table 4. Political cycles and CSR allocation

	Dependent variable: log(1 + CSR spending)		
	(1)	(2)	(3)
Drought (t-1)	0.104**	0.091**	0.080*
	(0.041)	(0.042)	(0.041)
Excess rain (t-1)	0.081	0.117*	0.116*
	(0.054)	(0.065)	(0.066)
Election year	0.014	0.060	
	(0.047)	(0.060)	
Pre-election year		0.108*	
		(0.064)	
Post-election year		-0.014	
		(0.069)	
Early election year			-0.020
			(0.079)
Late election year			0.110**
			(0.047)
Log population	3.676**	4.407**	4.310**
	(1.672)	(2.111)	(2.079)
Observations	4220	3615	3615
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Within R-squared	0.003	0.004	0.003

Notes: All columns use one-year-lagged drought and excess-rain indicators. Column (1) adds a contemporaneous state-assembly election-year indicator. Column (2) adds pre-election, election-year, and post-election indicators. Column (3) replaces the general election-year measure with early- and late-election timing indicators. Early election years are state assembly elections held in January through June; late election years are elections held in July through December. The reduction in observations in columns (2) and (3) reflects the requirement of lead history for the pre-election indicator. All models include district and year fixed effects. Standard errors clustered at the district level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 tests whether the lagged drought effect reflects political timing rather than climatic responsiveness, by adding election-cycle controls to the baseline specification.

Column (1) adds a contemporaneous state-assembly election-year indicator. The election-year coefficient is small and insignificant at 0.014, while the lagged drought coefficient remains positive and significant at 0.104.

Column (2) adds pre-election, election-year, and post-election indicators separately. The pre-election coefficient is positive and marginally significant at 0.108, suggesting some political timing in CSR allocation ahead of elections, while the lagged drought coefficient remains positive and statistically significant at 0.091. Column (3) separates election timing into early and late within the election year. Late election years are positively and significantly associated with higher CSR spending at 0.110, while early election years are not. This asymmetry is consistent with India's fiscal year (April–March) and typical CSR project lead times. CSR budgets are set at the start of the fiscal year in April, and project identification and disbursement typically take several months, so late-year elections (July–December) fall after firms have begun deploying their annual CSR budgets, while early-year elections (January–June) occur before this deployment is well under way.

Across all three specifications, the lagged drought coefficient remains positive and statistically significant, declining slightly from 0.104 in column (1) to 0.080 in column (3) as richer election controls are added. The late-election effect is robust to excluding the COVID-19 pandemic years 2020 and 2021, indicating that the result is not driven by the post-COVID expansion in mandatory CSR spending (Appendix Table A6).

Three findings emerge from the empirical analysis. First, same-year shock indicators are generally insignificant when estimated in isolation. The clearest result is that drought shocks are followed by higher CSR spending in the subsequent year. Excess rainfall effects are weaker overall but emerge at two-year lags. Some contemporaneous effects also emerge when current and lagged shocks are estimated jointly.

Second, the lagged response to both drought and excess-rain shocks is concentrated in poorer districts. The excess-rain poverty interaction also remains positive and consistently significant in joint specifications. Poverty appears to be a more robust moderator than agricultural dependence once both are included jointly.

Third, the lagged drought effect survives controls for election cycles. Some evidence of political-cycle effects in CSR allocation is visible, but election timing does not eliminate the lagged drought relationship.

Taken together, the results suggest that India's mandatory CSR regime is not an immediate shock-response mechanism, but it is not entirely static either. CSR spending adjusts with delay toward poorer districts affected by drought shocks, while the corresponding excess-rain response is smaller and less consistent. The drought result is sensitive to specification and does not extend to per-capita spending.

6. Conclusion

This paper asked whether India's mandatory CSR regime produces geographic reallocation toward districts experiencing adverse monsoon shocks. The analysis uses a balanced panel of 605 Indian districts from 2016 to 2023, exploiting within-district variation in monsoon rainfall.

CSR spending does not respond to same-year rainfall shocks, but a drought is associated with approximately 11 to 14 percent higher CSR spending in the following year, a result that is robust across the main specifications. The corresponding excess-rain response is positive but smaller and not statistically significant. At two-year lags, excess-rain effects become significant while drought effects fade to marginal significance, suggesting that drought produces the strongest response at the one-year horizon and excess rainfall at two years. The lagged response is concentrated in poorer districts. The poverty interaction is positive and significant for both drought and excess rainfall shocks, and district poverty is a stronger moderator of the response than agricultural dependence. India's mandatory CSR system is neither a pure shock-response mechanism nor entirely static. Spending adjusts with delay and partially toward districts facing climatic distress, but the adjustment is modest, concentrated in poorer districts, and sensitive to specification.

The analysis also finds evidence of political-cycle effects in CSR allocation. The lagged drought effect remains after controlling for election timing, suggesting it is not driven solely by political cycles. Late election years are nevertheless associated with higher CSR spending independently of rainfall conditions, indicating an independent association between election timing and CSR allocation.

These findings contribute to three bodies of work. First, the paper provides panel evidence that mandatory CSR spending responds to district-level monsoon shocks, extending a literature that has focused primarily on firm-level compliance and aggregate spending patterns. Second, it contributes to the rainfall shock literature by examining mandatory CSR spending as an underexplored response channel, one that operates with delay and is concentrated in poorer districts. Finally, it contributes to the political economy of resource allocation in India by showing that, under a mandatory spending regime, both electoral incentives and climatic shocks are independently associated with CSR allocation across districts.

Several limitations are important for interpreting the results. The identification strategy rests on the assumption that within-district monsoon variation is uncorrelated with unobserved determinants of CSR allocation, an assumption that is consistent with the placebo test but cannot be fully verified. The lagged drought effect does not survive per-capita scaling, leaving open whether per-resident CSR responds to drought. It also does not survive state-by-year fixed effects, making it difficult to fully separate the rainfall response from state-level time-varying confounders. The Poisson pseudo-maximum-likelihood specification also yields a small and insignificant lagged drought coefficient, indicating that the response does not translate into a comparable shift in aggregate CSR mass. The panel covers only 2016 to 2023, and the drought and excess-rain indicators are defined relative to each district's mean rainfall within this same period. The estimates therefore capture responsiveness to shocks that were anomalous within the sample window rather than relative to a longer historical baseline. Finally, the results are specific to India's mandatory CSR regime and may not generalise to other institutional or country settings.

Future work could examine whether the response is driven by specific CSR project categories, with health, rural development, and disaster relief as plausible channels. It could also explore whether responsiveness differs across firms, for example between firms with agricultural supply chains and those with stronger exposure to state-level political incentives. Linking firm-level disclosures to household-level outcomes would also allow a direct test of whether increased CSR spending translates into improved welfare for shock-affected households, a question that aggregate district-level CSR data alone cannot answer.

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8. Appendix

Table A1. Placebo test: future rainfall and CSR spending

	Dependent variable: log(1 + CSR spending)		
	(1)	(2)	(3)
Drought (t+1)	0.027	0.029	0.037
	(0.065)	(0.068)	(0.081)
Excess rain (t+1)	0.007	0.019	0.078
	(0.056)	(0.060)	(0.084)
Drought (t)		0.019	0.069
		(0.066)	(0.083)
Excess rain (t)		0.085	0.157**
		(0.069)	(0.078)
Drought (t-1)			0.113**
			(0.046)
Excess rain (t-1)			0.151*
			(0.083)
Log population	2.365*	2.282*	4.041**
	(1.281)	(1.254)	(1.987)
Observations	4220	4220	3615
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Within R-squared	0.001	0.001	0.005

Notes: Drought (t+1) and Excess rain (t+1) are one-year-ahead leads of the binary shock indicators, constructed from the lead of rain_z. Under the identifying assumption, future rainfall should not predict current CSR spending. Column (1) includes leads only. Column (2) adds contemporaneous shock indicators. Column (3) adds both contemporaneous and one-year-lagged indicators. All models include district and year fixed effects. Standard errors clustered at the district level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2. Robustness: state-by-year fixed effects

	Dependent variable: log(1 + CSR spending)		
	(1)	(2)	(3)
Drought (t)	0.062		0.070
	(0.067)		(0.080)
Excess rain (t)	0.148		0.246***
	(0.101)		(0.093)
Drought (t-1)		-0.023	-0.011
		(0.054)	(0.058)
Excess rain (t-1)		0.217**	0.239**
		(0.093)	(0.097)
Observations	4825	4220	4220
District FE	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes
Within R-squared	0.002	0.003	0.007

Notes: All columns replace year fixed effects with state-by-year fixed effects, absorbing all state-level time-varying confounders including state drought declarations, relief programme activation, and state political cycles. Column (1) estimates same-year shock indicators only. Column (2) estimates one-year-lagged shock indicators only. Column (3) includes both contemporaneous and lagged indicators jointly. All models include district fixed effects. Log population is omitted because it is largely absorbed by the district and state-by-year fixed effects. Standard errors clustered at the district level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3. CSR per capita robustness

	Dependent variable: log(1 + CSR per capita)		
	(1)	(2)	(3)
Drought (t)		0.025	0.048**
		(0.024)	(0.023)
Excess rain (t)		-0.035	-0.013
		(0.021)	(0.024)
Drought (t-1)	-0.006	-0.005	-0.015
	(0.021)	(0.022)	(0.027)
Excess rain (t-1)	-0.010	-0.014	-0.036*
	(0.018)	(0.019)	(0.020)
Drought (t-2)			0.002
			(0.025)
Excess rain (t-2)			-0.003
			(0.021)
Log population	-0.436	-0.379	0.331
	(0.440)	(0.445)	(0.562)
Observations	4220	4220	3615
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Within R-squared	0	0.002	0.003

Notes: Per-capita CSR is district CSR spending divided by district population. Column (1) re-estimates the lagged drought model using the per-capita outcome. Column (2) re-estimates the combined timing model using contemporaneous and lagged shock indicators. Column (3) re-estimates the persistence model including two-year lags. All models include district and year fixed effects. Standard errors clustered at the district level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4. CSR per capita robustness (excluding smallest 5% districts)

	Dependent variable: log(1 + CSR per capita)		
	(1)	(2)	(3)
Drought (t)		0.024	0.047*
		(0.024)	(0.024)
Excess rain (t)		-0.034	-0.015
		(0.022)	(0.025)
Drought (t-1)	7.77e-05	0.001	-0.009
	(0.023)	(0.024)	(0.029)
Excess rain (t-1)	-0.006	-0.011	-0.032
	(0.019)	(0.019)	(0.021)
Drought (t-2)			0.005
			(0.027)
Excess rain (t-2)			-0.002
			(0.022)
Log population	-0.450	-0.384	0.371
	(0.574)	(0.581)	(0.744)
Observations	4012	4012	3440
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Within R-squared	0	0.001	0.003

Notes: This table repeats the CSR per capita robustness analysis after excluding the smallest 5% of districts by population. The purpose is to reduce distortion from denominator instability in very small districts. All models include district and year fixed effects. Standard errors clustered at the district level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5. Robustness: Poisson pseudo-maximum-likelihood

	Dependent variable: CSR spending	
	(1)	(2)
Drought (t)		0.042*
		(0.023)
Excess rain (t)		-0.032
		(0.023)
Drought (t-1)	-0.026	-0.019
	(0.021)	(0.022)
Excess rain (t-1)	-0.002	-0.009
	(0.024)	(0.025)
Log population	0.254	0.302
	(0.536)	(0.531)
Observations	4220	4220
District FE	Yes	Yes
Year FE	Yes	Yes
Pseudo R-squared	0.901	0.901

Notes: Both columns re-estimate the corresponding Table 2 specifications using Poisson pseudo-maximum-likelihood (PPML), which models the conditional mean of CSR in levels rather than logs and is robust to heteroskedasticity (Correia, Guimarães and Zylkin, 2020). Column (1) mirrors Table 2 column (3) using one-year-lagged shock indicators only. Column (2) mirrors Table 2 column (4) with both contemporaneous and lagged indicators. Coefficients are semi-elasticities of the conditional mean of CSR. All models include district and year fixed effects. Standard errors clustered at the district level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6. Robustness: COVID-period exclusion for late-election result

	Dependent variable: log(1 + CSR spending)		
	(1)	(2)	(3)
Drought (t-1)	0.088**	0.145***	0.115**
	(0.039)	(0.052)	(0.047)
Excess rain (t-1)	0.087	0.118	0.122*
	(0.055)	(0.073)	(0.068)
Early election year	-0.060	0.058	-0.036
	(0.071)	(0.100)	(0.071)
Late election year	0.119**	0.115**	0.140**
	(0.047)	(0.055)	(0.055)
Log population	3.755**	3.269**	3.716**
	(1.721)	(1.548)	(1.713)
Observations	4220	3010	3615
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Within R-squared	0.003	0.004	0.004

Notes: All columns re-estimate the early- and late-election specification from Table 4 column (3). Column (1) reports the full-sample baseline. Column (2) excludes 2020 and 2021 to address the concern that the late-election result coincides with the post-COVID CSR expansion. Column (3) excludes 2020 only as a lighter exclusion. All models include district and year fixed effects. Standard errors clustered at the district level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.